Article

Ecological thermodynamic fluctuation and phase transition: A self-organized criticality-based framework for ecosystem responses to global warming

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Abstract
Current understanding of ecosystem responses to global warming remains predominantly anchored in element-process descriptions that focus on species distributions, phenological shifts, and productivity changes. While substantial empirical evidence documents warming-induced alterations across biological scales, existing frameworks exhibit fundamental limitations in explaining and predicting the widespread occurrence of abrupt ecological changes, regime shifts, and irreversible transitions. This paper argues that global warming, at its thermodynamic essence, constitutes a sustained injection of additional energy into the Earth's ecosystems accompanied by amplified energy fluctuations across multiple temporal scales. Ecosystems, as dissipative structures maintained far from thermodynamic equilibrium, respond to this energy perturbation according to principles rooted in non-equilibrium thermodynamics. I propose an "Ecological Thermodynamic Fluctuation-Phase Transition" framework that treats the intensity of warming-driven energy fluctuations as the governing control variable determining ecosystem response modalities. The framework advances three core propositions: first, enhanced energy fluctuations compress the attractor basin of the current steady state within an energy landscape, systematically reducing ecological resilience before any visible state change; second, when fluctuation intensity exceeds a critical threshold, the system is driven toward a self-organized critical state wherein any tiny perturbation can trigger cross-basin transitions, manifesting as ecological phase transitions; third, the direction of phase transition is guided by the maximum entropy production principle, with systems tending toward states characterized by faster energy dissipation, more rapid turnover, and structurally simplified configurations with higher entropy production rates. This framework is supported by metabolic scaling theory, statistical physics of critical phenomena, and thermodynamic extremal principles, and is realized through two novel indices: the Energy Sensitivity Index and the Phase Transition Warning Index. The theory provides a first-principles basis for unifying apparently disparate ecological responses to warming and offers a pathway toward predictive ecology grounded in energy and thermodynamics.

Keywords global warming; ecosystem response; non-equilibrium thermodynamics; energy fluctuation; steady-state transition; self-organized criticality; ecological phase transition.

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1 Introduction

1.1 From Gradual Change to Abrupt Transition: The Cognitive Challenge of Global Warming's Ecological Effects

Global mean surface temperature has increased by approximately 1.1°C above pre-industrial levels, with projections indicating further warming of 1.5°C to 4.4°C by the end of the twenty-first century depending on emission scenarios (IPCC, 2021). The ecological consequences of this warming trajectory manifest across all organizational scales, from individual physiology to biome distribution. Yet perhaps the most alarming and least predictable feature of ecosystem responses to warming is the recurrent observation of abrupt, nonlinear, and often irreversible ecological transitions (Zhang and Liu, 2012).

Empirical evidence for such abrupt changes continues to accumulate. The Amazon rainforest, historically a net carbon sink, has shown signs of reduced resilience and may be approaching a tipping point beyond which large-scale dieback becomes inevitable (Boulton et al., 2022). Between 10% and 47% of Amazonian forests may be threatened by increasing disturbances, risking a transition to degraded savanna-like states by 2050 (Flores et al., 2024). Coral reef ecosystems worldwide have experienced unprecedented bleaching events, with the fourth global coral bleaching event (2023–present) representing the most extensive and intensive thermal stress episode on record, affecting approximately 84.4% of the world's coral reef area (Wu and Zhang, 2012; Spady et al., 2026). Temperate marine ecosystems have undergone rapid climate-driven regime shifts; along the Australian coastline, extreme marine heat waves forced a 100-kilometer range contraction of extensive kelp forests, with temperate reef communities becoming dominated by persistent seaweed turfs and replaced by species characteristic of subtropical and tropical waters (Wernberg et al., 2016). In boreal and Arctic regions, permafrost thaw is accelerating, with abrupt thaw processes potentially affecting half of permafrost carbon through collapsing ground, rapid erosion, and landslides, even though abrupt thaw will probably occur in less than 20% of the permafrost zone (Turetsky et al., 2020).

These abrupt ecological changes share common features: they occur with limited early warning, they often exhibit hysteresis such that reversal requires substantially different conditions than those at which the transition occurred, and they carry profound consequences for ecosystem services, carbon cycling, and human well-being (Scheffer et al., 2009; Zhang, 2026e). Traditional ecological frameworks, which largely treat warming as a gradual directional pressure eliciting proportional responses, are fundamentally ill-equipped to anticipate, explain, or manage such discontinuous changes.

The prevailing approach to understanding ecological responses to warming has been to correlate biological variables—species distributions, phenological timing, primary productivity—with temperature trends and to project future states under various emission scenarios (Parmesan and Yohe, 2003; Pecl et al., 2017; Zhang, 2016a-b). While these efforts have yielded valuable insights into the breadth of ecological change already underway, they remain essentially descriptive and correlational. They cannot explain why some ecosystems exhibit gradual responses to warming while others undergo catastrophic collapse, nor can they predict the timing, direction, or magnitude of abrupt transitions. The challenge is therefore not merely to document ecological responses to warming (Rashid et al., 2015; Malik et al., 2018; Taju and Marelign, 2022; Saikia and Gori, 2024), but to develop a theoretical framework that can unify diverse observations under a common set of principles and generate testable predictions about future ecosystem trajectories.

1.2 The Deep Dilemma of Existing Response Frameworks

The limitations of current frameworks for understanding ecosystem responses to global warming operate at multiple levels. At the most fundamental level, existing approaches suffer from a scale disconnection problem: mechanisms identified at one organizational level, for instance, the temperature dependence of individual metabolic rate, cannot be straightforwardly aggregated to predict population, community, or ecosystem-level responses (Brown et al., 2004). Metabolic theory of ecology provides quantitative predictions for how metabolic rate varies with body size and temperature, and predicts how this rate controls ecological processes at all levels of organization from individuals to the biosphere (Brown et al., 2004). However the translation from individual metabolic responses to ecosystem-level phenomena involves complex interactions, feedbacks, and emergent properties that resist simple extrapolation.

Another limitation concerns the absence of a common currency that can integrate responses across diverse ecological phenomena. Warming simultaneously affects metabolic rates, water balance, nutrient cycling, species interactions, and disturbance regimes. Each of these effects is typically studied within its own disciplinary framework, employing distinct metrics and theoretical traditions. The result is a fragmented understanding in which the coherence of the system's response is lost. What is needed is a common measure—a fundamental quantity that all ecological processes share and that can serve as the basis for comparing, aggregating, and predicting responses across scales. Energy, as the universal currency of all biological and ecological processes, offers precisely this potential (Zhang, 2026d).

The deeper limitation is the near-total absence of first-principles reasoning in mainstream global change ecology. The field has been dominated by empirical approaches: observational studies documenting ongoing changes, experimental manipulations such as warming chambers and free-air CO_2 enrichment, and process-based simulation models parameterized from empirical relationships. While enormously valuable, these approaches do not derive ecosystem behavior from fundamental physical laws. They cannot answer the question of why ecosystems respond to warming in the ways they do, rather than in some other conceivable way. A first-principles framework grounded in thermodynamics, specifically, in the non-equilibrium thermodynamics of open systems (Zhang, 2013, 2016), may provide the foundation that current approaches lack.

1.3 Research Objectives and the Fundamental Question

This paper addresses a single overarching question: Does there exist a first-principles framework, grounded in energy and thermodynamics, that can explain the intensity, direction, threshold behavior, and hysteresis of ecosystem responses to global warming?

The objectives of this paper are threefold: (1) I conduct a comprehensive synthesis of the multi-level evidence for ecosystem responses to global warming, identifying patterns, commonalities, and the conditions under which gradual versus abrupt responses occur. (2) I critically evaluate existing theoretical frameworks, identifying their explanatory successes and, more importantly, their logical gaps and empirical failures. (3) Most importantly, I propose and systematically develop an innovative theoretical framework—the Ecological Thermodynamic Fluctuation-Phase Transition framework (Fig. 1), that treats ecosystems as non-equilibrium dissipative structures and explains their responses to warming in terms of energy fluctuation amplification, basin compression in energy landscapes, self-organized criticality, and entropy-production-guided phase transitions (Zhang, 2013, 2016, 2026e; Appendix).

The central argument is that global warming, understood thermodynamically as a perturbation to the energy balance and energy fluctuation regime of ecosystems, drives systems toward critical thresholds. The crossing of these thresholds manifests as ecological phase transitions: abrupt, often irreversible reorganizations of ecosystem structure and function, that toward states characterized by higher rates of energy dissipation and entropy production (Zhang, 2013, 2016, 2026e). This argument is developed through rigorous integration of metabolic ecology, non-equilibrium thermodynamics, statistical physics, and empirical observations of ecosystem transitions, yielding a framework that is both mechanistically grounded and operationally testable.

2 Research Review and Knowledge System Assessment

2.1 Multi-Level Evidence of Ecosystem Responses

2.1.1 Individual and Population-Level Responses

The most fundamental biological response to warming operates at the level of individual metabolism. The metabolic theory of ecology provides a quantitative framework for understanding how metabolic rate scales with body size and temperature (Brown et al., 2004). This theory builds on the observation that metabolic rate follows Kleiber's law, scaling as body mass raised to the three-quarters power, and that the temperature dependence of metabolic rate follows the Arrhenius equation, with metabolic processes accelerating exponentially with increasing temperature within the range approximately 0°C to 40°C (Gillooly et al., 2001).

The metabolic theory of ecology holds that the rate at which power can be delivered to the cells of bodies scales with body size and temperature according to power laws, and the scaling with temperature follows the Arrhenius equation (Brown et al., 2004). This has profound implications for individual organisms under warming. Increased metabolic rates elevate maintenance costs, reducing the net energy available for growth, reproduction, and storage. The consequence is a systematic compression of net energy surplus, which manifests across diverse taxa as reduced body size, altered life history strategies, and shifts in energy allocation patterns (Sheridan and Bickford, 2011).

One of the most consistently documented responses to warming is the reduction in organismal body size, a phenomenon encapsulated in the temperature-size rule (Atkinson, 1994). The temperature-size rule describes the tendency for ectotherms to develop faster but mature at smaller body sizes at higher temperatures, with reductions of as much as 20% smaller body size for a 10°C temperature increase (Atkinson, 1994). Warming generally leads to reduced body size of ectotherms, with the temperature-size rule representing a widespread pattern of phenotypic plasticity whereby animals grow faster but reach a smaller adult size under warming (Gardner et al., 2011). Body-size reductions with warming are stronger in aquatic taxa than in terrestrial taxa (Forster et al., 2012). Declining body size has been proposed as a third universal response to warming, alongside range shifts and phenological changes, with implications for individual fitness, population dynamics, and ecosystem functioning (Gardner et al., 2011).

The ecological significance of body size reduction extends well beyond the individual. Body size governs metabolic rate, which in turn determines resource consumption rates, nutrient excretion rates, and susceptibility to predation. When body sizes systematically decline across entire communities, the trophic structure and energy flow architecture of the ecosystem are fundamentally altered. This connects individual-level metabolic responses to community and ecosystem-level phenomena through the energetic constraints that body size imposes.

2.1.2 Community-Level Responses

At the community level, warming drives species redistribution, compositional reorganization, and biotic homogenization. Species redistribution in response to climate change is a global phenomenon (Zhang, 2026a-b). For marine, freshwater, and terrestrial species alike, the first response to changing climate is often a shift in location to stay within preferred environmental conditions (Pecl et al., 2017). Meta-analyses demonstrate that, on average, terrestrial taxa move poleward by approximately 17 km per decade and upward in elevation by approximately 11 m per decade (Chen et al., 2011). Ectotherms show stronger range shift responses to ongoing climate change than endotherms, and the higher the latitude, the greater the latitudinal range shift (Ramalho et al., 2023).

However, species redistribution is not a simple, uniform process. Approximately half of studied species show range shifts in expected directions, with 49.7% of species shifting poleward, while others show no shift or even shifts in unexpected directions (Rubenstein et al., 2023). In tropical regions, documented climate-driven species range shifts have been exclusively upslope, with no evidence of poleward shifts, a pattern attributed to the lack of latitudinal temperature gradients within the tropics (Colwell and Feeley, 2025). This spatial heterogeneity in responses complicates prediction and underscores the need for mechanistic rather than purely correlational understanding.

Community composition is shifting toward thermophilic assemblages, a process known as thermophilization. The ongoing climate change is triggering plant community thermophilization, a selection process that shifts community composition toward species adapted to warmer climates (Borderieux et al., 2024). However, the relationship between thermophilization and biotic homogenization is complex. While thermophilization is widely observed, it does not necessarily trigger homogenization in all systems; extinction, rather than colonization, appears to drive recent thermophilization in some forest understory communities (Borderieux et al., 2024). Warming drives biotic impoverishment and homogenization in some systems, decreasing α-diversity and β-diversity of plant communities at taxonomic, functional, and phylogenetic levels (Zhu et al., 2026).

Phenological shifts represent another dimension of community reorganization. Climate change has altered the timing of recurring biological cycles in both plants and animals, and phenological changes may be unequal within and among trophic levels, potentially impacting the intricate interactions that regulate ecosystem functioning (Lang et al., 2025; Sundar, 2013; Sundar et al., 2017; Mishra et al., 2021). Future warming may increase phenological asynchronization between plants and animals and potentially disturb trophic interactions and ecosystem stability (Lang et al., 2025). Phenological mismatches induced by climate change between birds and insects can degrade ecosystems through trophic cascades, demonstrating how temporal decoupling of species interactions propagates through ecological networks (Fang et al., 2026).

2.1.3 Ecosystem Function Responses

At the ecosystem level, warming affects carbon cycling, nutrient dynamics, and overall productivity in ways that exhibit pronounced nonlinearity and context dependence. Net primary production shows complex, nonlinear responses to warming. Analyses of grassland productivity reveal a ridge-shaped response surface in which net primary production is humped, exhibiting a unimodal response to temperature and precipitation, with peak NPP rising under elevated CO_2 or nitrogen but also shifting to lower temperatures (Zhu et al., 2016). This nonlinearity indicates that the same magnitude of warming can have opposite effects on productivity depending on the starting temperature and co-limiting resources.

The carbon balance of ecosystems under warming depends critically on the differential temperature sensitivities of photosynthetic carbon uptake and respiratory carbon release. The long-term temperature dependence of ecosystem respiration is significantly stronger than that of gross primary production, resulting in a temperature-dependent metabolic balance wherein the ratio of respiration to production increases with warming (Yvon-Durocher et al., 2012). Both gross primary production and ecosystem respiration are consistently elevated in warmed treatments, but the magnitude of increase in ecosystem respiration between warmed and unheated systems is markedly greater than the increase in gross primary production, reflecting its stronger temperature dependence (Yvon-Durocher et al., 2010). Forest production efficiency increases with growth temperature, indicating that forests can partially compensate for warming-induced respiratory losses through enhanced photosynthetic efficiency (Collalti et al., 2020).

The temperature sensitivity of soil respiration is a critical parameter governing the strength of the carbon-climate feedback. The Q_{10} coefficient, describing the proportional change in soil respiration with a 10°C increase in temperature, shows substantial variation across ecosystems and between autotrophic and heterotrophic components (Yu et al., 2017). Temperature sensitivities of autotrophic and heterotrophic respiration vary with time scales of investigation, and the Q_{10} of autotrophic respiration is generally higher than that of heterotrophic respiration across different forest types (Shi et al., 2012). This differential sensitivity has important implications for predicting how ecosystem carbon balance will respond to future warming.

Thermal acclimation adds further complexity. Model-based assessments show that ecosystem-level photosynthesis and autotrophic respiration exhibit significant thermal acclimation, with temperature sensitivities being linearly decreased with warming (Ma et al., 2023). Using thermal-acclimated parameter values, simulated gross primary production, net primary production, and plant autotrophic respiration are all lower than those simulated with non-thermal acclimated parameter values, while ecosystem respiration simulated with thermal-acclimated parameter values is higher, resulting in greater net carbon release (Ma et al., 2023). This suggests that peatlands are likely to release more carbon than previously estimated, and Earth system models may overestimate carbon uptake by peatlands under warming if physiological thermal acclimation is not incorporated (Ma et al., 2023).

Nutrient cycling is profoundly affected by warming. Simulations show substantial increases in nitrogen and phosphorus mineralization with climate warming and consequent increases in nutrient availability to plants, with distinctly different changes in nitrogen versus phosphorus cycles in response to warming (Jiang et al., 2016). Climate change impacts nutrient dynamics around the globe and exacerbates contemporary water-quality challenges, with greater nitrogen and phosphorus mineralization, nitrogen deposition, and leaching rates observed under warming (Costa et al., 2023). Extreme temperature events can decouple microbial carbon, nitrogen, and phosphorus cycling, with differential resistance and resilience of these elemental cycles to transient but severe temperature disturbances (Mooshammer et al., 2017; Zhnag, 2026d-e).

2.2 Steady-State Transitions and Critical Threshold Theory

The observation that ecosystems can undergo abrupt, persistent shifts between alternative stable states has become a cornerstone of modern ecology (Zhang, 2026e). Shallow lakes provide the archetypal example: they can exist in either a clear-water, macrophyte-dominated state or a turbid, phytoplankton-dominated state under the same external nutrient loading, with transitions between these states exhibiting hysteresis (Scheffer et al., 1993). The concepts of ecosystem regime shifts, thresholds, and alternative or multiple stable states are used extensively in the ecological and environmental management literature (Capon et al., 2015; Zhang, 2026e). However, empirical evidence for regime shifts and changes between multiple or alternative stable states is mainly limited to studies of shallow temperate lakes, and most studies using such terms lack convincing evidence or appropriate data (Capon et al., 2015).

The theoretical foundation for understanding regime shifts is built on bifurcation theory and dynamical systems analysis (Zhang, 2013, 2016). A climate tipping point occurs when a small change in forcing triggers a strongly nonlinear response in the internal dynamics of part of the climate system, qualitatively changing its future state (Lenton et al., 2008). Recent work shows that early warning of an approaching climate tipping point is possible in principle, and could have considerable value in reducing the risk that such tipping points pose (Lenton, 2011).

Critical slowing down has emerged as the most theoretically grounded early warning signal for impending critical transitions. As a system approaches a bifurcation point, the rate of recovery from small perturbations becomes progressively slower, manifesting in statistical signatures including increasing variance, rising autocorrelation, and enhanced flickering between alternative states (Scheffer et al., 2009; Zhang, 2026e). These early warning signals have been successfully identified in warnings of historical abrupt climate shifts, although masking and false signals can obscure genuine critical slowing down signals, potentially leading to missed warnings (Dakos et al., 2015).

The application of landscape-flux theory from non-equilibrium statistical mechanics provides a more general framework for quantifying the global stability of ecological systems and for providing warning signals for critical transitions. The average flux as the non-equilibrium driving force, the entropy production as the thermodynamic driving force, and time irreversibility of cross-correlation functions can serve as warning signals for critical transitions between alternative stable states much earlier than other conventional predictors (Xu et al., 2023). For complex systems subject to random noise, the driving force of the system can be profitably decomposed into the gradient of the potential landscape and the curl flux, providing a unified description of both equilibrium-like and non-equilibrium dynamics (Xu et al., 2023).

2.3 Metabolic Ecology and Energy Equivalence Principles

The metabolic theory of ecology represents one of the most ambitious attempts to provide a unified theoretical foundation for ecology. Its central proposition is that metabolic rate, i.e., the rate at which organisms take up, transform, and expend energy and materials, governs most biological rates and times, from the molecular to the global scale (Brown et al., 2004). The theory predicts that metabolic rate scales with body mass raised to the three-quarters power and with temperature according to the Boltzmann-Arrhenius factor, forming the quantitative basis for understanding how warming affects biological processes.

The theoretical foundation of metabolic scaling lies in the fractal-like design of resource distribution networks. The universal three-quarters power scaling of metabolic rate with body mass emerges from the optimization of space-filling, branching networks that distribute resources to all cells, with the scaling exponent deriving from the geometry and hydrodynamics of these networks (West et al., 1997). The temperature dependence of metabolic rate, described by the Arrhenius equation, reflects the kinetic energy required to overcome activation barriers in biochemical reactions, with an average activation energy of approximately 0.6 to 0.7 eV for aerobic metabolism (Gillooly et al., 2001).

The metabolic theory of ecology extends beyond individual organisms to explain large-scale ecological patterns. Specifically, the theory predicts that the number of species increases exponentially with increasing environmental temperature, and more quantitatively, that log-transformed number of species varies linearly with the reciprocal of absolute temperature, with the slope of the relationship ranging between -0.70 and -0.60 (Wang et al., 2009). While the metabolic theory of ecology has generated widespread attention and controversy, it is quite different from conventional regression-based methods because of its biological mechanism-sound approach (Wang et al., 2009).

The ecological significance of metabolic scaling for understanding warming responses lies in the concept of net energy surplus. Individual organisms must allocate assimilated energy among maintenance, growth, reproduction, and storage. Maintenance metabolism, being temperature-dependent, rises with warming, while assimilation through photosynthesis or consumption may not increase proportionally. The result is a compression of the net energy surplus, the energy available for all processes beyond basal maintenance. When net energy surplus approaches zero, organisms cannot sustain populations, and ecosystem-level consequences cascade through trophic networks.

2.4 Non-Equilibrium Thermodynamics in Ecology: Nascent Applications

The application of thermodynamic principles to ecological systems has a history extending over several decades, rooted in the recognition that ecosystems are open, far-from-equilibrium systems maintained by continuous energy flow. Ilya Prigogine’s theory of dissipative structures provides the conceptual foundation: systems driven far from equilibrium can self-organize into what he termed dissipative structures, and the complex mechanisms of life cannot be sustained in thermodynamic equilibrium but emerge only as a result of steady processes running far enough from equilibrium (Prigogine and Stengers, 1984; Zhang, 2013, 2016). Prigogine defined dissipative structures as giant fluctuations in thermodynamically open systems that operate far from thermodynamic equilibrium and exchange energy, matter, and information with the external environment (Prigogine, 1977).

Schneider and Kay advanced the thermodynamic understanding of life by proposing that life is a response to the thermodynamic imperative of dissipating gradients. Organisms composing terrestrial ecosystems acquire and degrade solar energy or its derivatives, thereby reducing the thermal gradient impressed on Earth by the Sun; Kay and Schneider call this the thermodynamic imperative of the restated second law for open systems (Schneider and Kay, 1994). This perspective views ecosystems as gradient dissipators, with more mature ecosystems degrading available energy gradients more completely and at faster rates.

Jørgensen developed a comprehensive thermodynamic theory for ecosystems centered on the concept of exergy, defined as the work the system can perform when it is brought into equilibrium with the environment. The hypothesis, as a basis for the ecosystem theory, may be formulated as follows: a system that receives a flow of exergy will utilize this flow to move away from thermodynamic equilibrium; if more combinations of components and processes are offered, the one that moves the system furthest from thermodynamic equilibrium under the prevailing conditions will be selected (Jørgensen, 1999). The introduction of the concept of exergy makes it possible to give a more profound and comprehensive explanation of the ecosystem's reactions and growth patterns (Jørgensen and Svirezhev, 2004).

The maximum entropy production principle represents perhaps the most ambitious thermodynamic extremal principle proposed for ecological systems. The maximum entropy production principle posits that ecosystems produce entropy at the maximum possible rate, and this principle has been argued to arise from non-equilibrium thermodynamics (Kleidon and Lorenz, 2005; Zhang, 2012, 2018). Maximum entropy production provides a new guiding principle for modeling the flows of energy and matter between plants, ecosystems, and their environment, and offers a novel thermodynamic perspective on the origin and evolution of life (Dewar et al., 2013). However, these principles are not robustly based in physical theory and suffer from treating complex ecosystems in an extremely coarse manner (Meysman and Bruers, 2010). Empirical tests show that the living state shows always an increased entropy production over the abiotic state, but the state selection and gradient response hypotheses break down when the food web incorporates more than one trophic level, indicating that they are not generally valid (Meysman and Bruers, 2010).

Forest ecosystems represent vivid examples of open non-equilibrium systems. The existence of extreme principles in ecological thermodynamics is a subject of discussion in the works of many physicists, ecologists, and researchers dealing with non-equilibrium thermodynamics (Lisitsyn et al., 2024). Ecosystems approach, but do not reach, maximum entropy production, and the relationship between succession and entropy production depends on vegetation characteristics (Lisitsyn et al., 2024).

Energy dissipation has been empirically linked to ecosystem development. The ecosystem exergy theory hypothesizes that energy dissipation increases with ecosystem maturity, and empirical tests combining theoretical simulations and thermal remote sensing observations confirm that energy dissipation increases in succession from non-vegetated land to forests (Maes et al., 2011). Higher energy dissipation is obtained through increased evapotranspiration or increased surface roughness, two aspects generally related with succession in terrestrial ecosystems (Maes et al., 2011).

Ecological succession can be described by the second law of thermodynamics. According to the universal law of maximal energy dispersal, an ecosystem evolves toward a stationary state in its surroundings by consuming free energy via diverse mechanisms, with the process proceeding along the direction of decreasing the rate of dissipation per biomass (Würtz and Annila, 2010). Thermodynamically, ecosystem growth is the increase of energy throughflow and stored biomass, and ecosystem development is the internal reorganization of these energy mass stores, which affect transfers, transformations, and time lags within the system (Fath et al., 2004).

2.5 The Critical Gap

Despite these substantial bodies of theory and evidence, a critical gap remains: the lack of a systematic theoretical integration that connects short-term warming perturbations to the long-term dynamics of energy-fluctuation-driven ecological phase transitions. Metabolic theory explains how temperature affects individual rates but does not address how these individual effects aggregate to ecosystem-level stability properties. Regime shift theory describes the phenomenology of abrupt transitions but does not derive them from thermodynamic first principles. Ecological thermodynamics provides extremal principles that may govern long-term ecosystem development but has not been realized for predicting transient responses to global warming. What is needed is a framework that bridges these domains: a theory that explains how the energy perturbations imposed by global warming drive ecosystems toward thermodynamic instability and phase transitions, yielding testable predictions about when, where, and how such transitions will occur.

3 Gaps and Logical Deficiencies in Existing Theories

3.1 The Bankruptcy of Linear Warming-Response Thinking

The dominant paradigm in global change ecology has been implicitly linear: a given magnitude of warming is expected to produce a proportional response in ecological variables. This expectation is embedded in the structure of species distribution models that project range shifts based on climate envelopes, in dynamic vegetation models that adjust productivity parameters as functions of temperature, and in empirical studies that report correlations between temperature trends and ecological changes.

The empirical record decisively refutes this linear expectation. Ecosystem responses to warming are replete with thresholds, hysteresis, and path dependence. Coral reefs persist with apparently normal function until a thermal threshold is crossed, at which point mass bleaching and mortality occur within weeks (Hughes et al., 2018). Shallow lakes maintain clear-water states despite increasing nutrient loading until a critical concentration is exceeded, whereupon they flip rapidly to turbid conditions and resist restoration even when nutrient levels are substantially reduced (Scheffer et al., 1993). Boreal forests exhibit apparent stability for decades under warming before sudden, widespread mortality events triggered by the coincidence of drought and heat (Allen et al., 2010). Permafrost peatlands undergo gradual warming for extended periods before abrupt thermokarst formation radically restructures hydrology, vegetation, and carbon dynamics (Turetsky et al., 2020).

These phenomena share a common mathematical structure: they are characteristic of systems possessing alternative stable states separated by potential barriers. The transition between states is not proportional to the magnitude of forcing but rather depends on whether the forcing pushes the system across a threshold. Once crossed, the transition may be self-reinforcing through positive feedbacks, and reversal may require forcing conditions substantially different from those at which the initial transition occurred. Linear or weakly nonlinear models cannot capture this dynamics.

The inadequacy of linear thinking extends to the very conceptualization of what warming means for ecosystems. Warming is typically characterized by mean annual temperature change, occasionally supplemented by metrics of extreme temperature frequency. But ecosystems do not experience mean annual temperature; they experience the diurnal, seasonal, and interannual variation in the energy fluxes that drive biological processes. The translation from atmospheric temperature to biologically effective energy input involves radiation balance, latent heat exchange, soil moisture mediation, and canopy structure effects. A framework that treats temperature rather than energy as the primary driver misses the thermodynamic essence of what warming actually means for the living system.

3.2 The Persistent Absence of an Energy Perspective

The most significant theoretical gap in current understanding is the absence of energy as a unifying explanatory variable (Zhang, 2026d-e). Global warming is, fundamentally, a perturbation to the Earth’s energy balance. Anthropogenic greenhouse gas emissions reduce the rate at which longwave radiation escapes to space, increasing the energy retained within the Earth system. This additional energy is partitioned among atmospheric heating, ocean heat uptake, ice melt, and (crucially for ecology) the energy available to drive biological and ecological processes.

Mainstream ecological theory continues to treat temperature, rather than energy flow, as the primary independent variable. This is a category error with profound consequences. Temperature is a state variable: a measure of the average kinetic energy of molecules, while energy flow is a process variable: a measure of the rate at which work-capable energy moves through the system. Ecosystems are organized and maintained by energy flow, not by temperature per se. The distinction matters because the same temperature can correspond to vastly different energy flow regimes depending on humidity, radiation, wind speed, and vegetation structure. Conversely, different temperature regimes can support similar energy flow regimes if compensating factors are present.

Reframing the question in terms of energy rather than temperature yields fundamentally different insights. The relevant question is not how many degrees of warming a system can tolerate before changing, but rather how much additional energy the system can dissipate through its existing structure before that structure must reorganize. This reframing connects ecological responses directly to thermodynamic constraints and opens the door to a first-principles understanding.

3.3 Fundamental Questions That Cannot Be Answered

The deficiencies of existing frameworks are most starkly revealed by their inability to answer several fundamental questions.

Why do some ecosystems respond to the same magnitude of warming with enhanced productivity while others collapse? Temperature increase alone cannot explain this divergence. The metabolic theory of ecology predicts increased metabolic rates under warming, which could theoretically increase productivity if resource supply keeps pace. But in many systems, warming simultaneously increases respiratory carbon losses and water stress, leading to net carbon loss. The outcome depends on the balance between energy-driven processes, i.e, production and respiration, and on the system’s capacity to dissipate the additional energy without structural reorganization. This energy-balance perspective is absent from most analyses.

Why does resilience loss often precede visible ecological change? Empirical observations and theoretical models demonstrate that systems approaching critical transitions exhibit declining recovery rates from perturbations long before any change in the mean state is detectable (Scheffer et al., 2009). This phenomenon of critical slowing down indicates that the stability properties of the system are eroding even as the system appears unchanged. The thermodynamic interpretation, that the attractor basin is being compressed by increasing energy fluctuations, provides a mechanistic explanation for this otherwise puzzling observation.

What determines the direction of an ecological phase transition? When a system crosses a threshold and reorganizes into a new state, what determines the characteristics of that new state? Existing regime shift theory describes the existence of alternative basins of attraction but does not explain why one basin rather than another is selected. I argue that thermodynamic extremal principles, specifically, the tendency toward maximum entropy production, provide the selection criterion. Systems undergoing phase transitions tend to move toward states that dissipate energy more rapidly, explaining the widespread observation that warming-disturbed ecosystems are characterized by faster turnover, simplified structure, and dominance by opportunistic, rapidly metabolizing species.

4 Theoretical Innovation: The Ecological Thermodynamic Fluctuation-Phase Transition Framework

4.1 Core Concepts and Fundamental Assumptions

The framework I propose rests on a single fundamental assumption: ecosystems are dissipative structures maintained far from thermodynamic equilibrium (Zhang, 2013, 2016) by the continuous throughput of energy, and global warming constitutes a systematic perturbation to both the mean and the variance of this energy throughput. From this assumption, a coherent theoretical structure emerges that can explain the full range of observed ecosystem responses to warming (Fig. 1; Appendix).

The concept of ecosystems as dissipative structures draws directly on Prigogine‘s foundational insight that systems maintained far from equilibrium by energy flow can exhibit self-organization, developing ordered structures that dissipate energy more effectively than disordered configurations (Prigogine and Stengers, 1984; Zhang, 2013, 2016). An ecosystem: a forest, a coral reef, and a grassland, is precisely such a structure. Solar radiation, the primary energy source for most ecosystems, creates a gradient between the hot sun and cold space. Photosynthesis captures a fraction of this energy and converts it to chemical form, initiating a cascade of energy transformations through trophic networks, eventually dissipating the captured energy as heat. The structure of the ecosystem: its species composition, biomass distribution, trophic organization, and nutrient cycling architecture, represents a particular configuration of matter organized to capture, transform, and dissipate this energy flow.

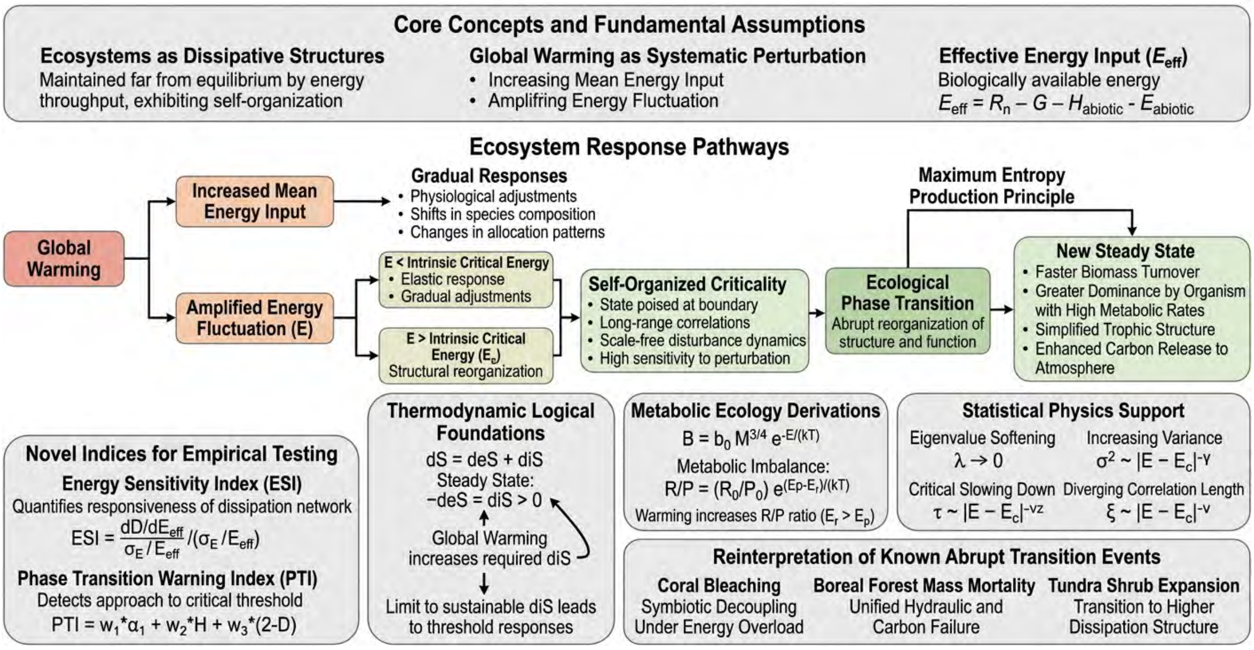

Fig. 1 Systematic diagram for the non-equilibrium thermodynamic framework for ecosystem responses to global warming.

Global warming perturbs this energy flow regime in two distinct but interacting ways. First, it increases the mean energy input to the system. The enhanced greenhouse effect increases downwelling longwave radiation, raising surface temperatures and, all else being equal, increasing the energy available to drive biological processes. Second, and perhaps more importantly, it amplifies the variance of energy input. Climate change is increasing the frequency, intensity, and duration of extreme events including heatwaves, droughts, and heavy precipitation (Zhang and Liu, 2012; IPCC, 2021). These extremes represent pulses of energy input that can be substantially larger than the system‘s evolved capacity to dissipate them through existing structures.

The distinction between mean and variance effects is crucial. A moderate increase in mean energy input may be accommodated by existing ecosystem structures through physiological adjustments, shifts in species composition, or changes in allocation patterns. These are the gradual responses that dominate the literature. But a sufficiently large increase in energy fluctuation, i.e., a heatwave that pushes temperatures beyond physiological tolerance, a drought that reduces latent heat cooling below critical levels, can overwhelm the system's dissipative capacity, triggering structural reorganization. These are the abrupt responses, i.e., the regime shifts, the mass mortality events, the ecosystem collapses that current frameworks struggle to explain (Zhang, 2026e).

4.2 Core Concept Definitions

To realize this framework, several core concepts must be precisely defined.

Effective Energy Input (E_{eff}): the biologically available energy that an ecosystem receives and can potentially dissipate through its metabolic and physical processes. It is not simply incident solar radiation, but rather the net energy after accounting for reflection, re-radiation, latent heat exchange, and other non-biological dissipation pathways. Mathematically, effective energy input can be expressed as:

$$E_{\mathrm{eff}} = R_n - G - H_{\mathrm{abiotic}} - \lambda E_{\mathrm{abiotic}}$$

where R_n is net radiation, G is ground heat flux, H_{abiotic} is abiotic sensible heat flux, and $\lambda E_{\mathrm{abiotic}}$ is abiotic latent heat flux. The biologically mediated components of sensible and latent heat flux, along with the chemical energy stored in biomass, constitute the energy that the ecosystem dissipates through its living structure.

Ecological Temperature (T_{eco}): a composite measure that integrates the thermodynamic temperature with the modifying effects of water availability, nutrient limitation, and other factors that determine the fraction of thermal energy that can actually drive biological processes. It recognizes that a given thermodynamic temperature can correspond to very different biological energy availability depending on context. A desert at 30°C and a tropical rainforest at 30°C represent vastly different ecological energy regimes: the desert has abundant thermal energy but insufficient water to transduce that energy into biological work, while the rainforest has both the thermal energy and the water necessary to support high biological energy throughput.

Energy Fluctuation (ΔE): the temporal variability in effective energy input across time scales. It can be quantified as the standard deviation of de-trended effective energy input over a relevant time window, but more sophisticated characterizations include the power spectrum of energy input fluctuations and metrics of extreme event frequency and intensity. The critical insight is that what matters for ecosystem stability is not just the mean energy input but the amplitude and frequency distribution of fluctuations around that mean.

Energy Landscape: a conceptual construct that maps the stability properties of alternative ecosystem configurations in terms of effective energy input and its fluctuation characteristics. Drawing on the formal analogy with potential landscapes in statistical physics, the energy landscape represents the effective free energy of different ecosystem states as a function of energy forcing conditions. Stable states correspond to local minima in this landscape, with the depth of the basin representing resilience—the magnitude of perturbation required to displace the system from that state. The energy landscape is not static but evolves as species composition, biomass, and soil properties change.

Intrinsic Critical Energy (E_c): is the maximum energy fluctuation amplitude that a given ecosystem configuration can absorb without undergoing structural reorganization. It is a system-specific threshold determined by the physiological tolerances of component species, the buffering capacity of the physical environment, and the redundancy and modularity of the energy dissipation network. When the energy fluctuation amplitude exceeds the intrinsic critical energy, the system is pushed beyond its capacity for elastic response, and structural reorganization becomes inevitable.

Self-Organized Criticality: in the ecological context refers to the tendency of ecosystems subjected to sustained energy forcing to evolve toward a critical state poised at the boundary between stability and instability. In this state, energy dissipation occurs through avalanches of all sizes, with the size distribution following a power law. The concept, originally developed by Bak and colleagues to explain the ubiquity of fractal scaling and power-law distributions in nature (Zhang, 2012, 2016, 2018), provides a natural framework for understanding why ecosystems exhibit intermittent, scale-free disturbance dynamics (Bak et al., 1987).

4.3 Three Original Propositions

Building on the core concepts defined above, I propose three original propositions that constitute the theoretical core of the Ecological Thermodynamic Fluctuation-Phase Transition framework.

Proposition One: Fluctuation Amplification and Basin Compression

Global warming, by simultaneously increasing mean energy input and amplifying energy fluctuations, systematically compresses the attractor basin of the current ecosystem steady state within the energy landscape, reducing resilience before any visible state change occurs.

This proposition rests on a thermodynamic argument. The attractor basin, the region of the energy landscape within which the system returns to its equilibrium configuration following perturbation, is maintained by the balance between energy-driven disruptive forces and the structural stabilizing forces of the ecosystem. Disruptive forces arise from the energy that must be dissipated: metabolic heat production, evapotranspiration, and the kinetic energy of biological processes. Stabilizing forces arise from the feedbacks that maintain ecosystem structure: competitive exclusion, predator-prey regulation, nutrient retention mechanisms, and the physical structure of vegetation.

When mean energy input increases, disruptive forces intensify. Higher temperatures increase metabolic rates across all trophic levels, increasing the energy that must be dissipated. This alone compresses the basin somewhat. But the more significant effect comes from fluctuation amplification. Extreme energy pulses: heatwaves, droughts, and intense precipitation events, can temporarily overwhelm dissipative capacity. Even if the system eventually recovers from each individual pulse, the cumulative effect is to erode the stabilizing feedbacks. Species with narrower physiological tolerances are eliminated (Zhang, 2026a-b). Nutrient pools are depleted. Soil organic matter is oxidized. Physical structure is damaged. Each event makes the system slightly less capable of dissipating the next event, creating a positive feedback loop that progressively compresses the attractor basin.

This basin compression manifests empirically as critical slowing down, i.e., the increasing recovery time from perturbations that is the most robust early warning signal of approaching critical transitions (Scheffer et al., 2009). The thermodynamic mechanism proposed here provides the physical basis for this statistical signature: critical slowing down occurs because the energy landscape basin is becoming shallower, reducing the restorative force that returns the system to equilibrium.

A mathematical formalization of basin compression can be expressed through the dynamics of the energy landscape. Let the effective potential $V(x, E_{\mathrm{eff}})$ represent the energy landscape as a function of the system state variable x and the effective energy input E_{eff}. The dynamics of the system can be written as:

$$\frac{dx}{dt} = -\frac{\partial V(x, E_{\mathrm{eff}})}{\partial x} + \sigma(E_{\mathrm{eff}}) \cdot \xi(t)$$

where $\sigma(E_{\mathrm{eff}})$ is the amplitude of stochastic fluctuations, which increases with effective energy input, and $\xi(t)$ represents uncorrelated Gaussian noise. As E_{eff} increases, the potential well becomes shallower, i.e., the curvature $\partial^2 V/\partial x^2$ at the equilibrium point decreases, while simultaneously the fluctuation amplitude σ increases. Both effects reduce the mean first passage time for escape from the basin, making a transition increasingly likely.

Proposition Two: Self-Organized Criticality and Phase Transition Triggering

When energy fluctuation intensity exceeds the intrinsic critical energy: when the amplitude of effective energy input fluctuations surpasses the system's capacity for elastic dissipation, the ecosystem is driven toward a self-organized critical state. In this state, the system exhibits long-range spatial and temporal correlations, and any arbitrarily small perturbation can trigger a cross-basin transition, manifesting as an ecological phase transition (Zhang, 2016, 2026e).

The mechanism underlying this proposition draws on the theory of self-organized criticality as developed in statistical physics (Bak et al., 1987). Systems that are slowly driven by energy input and have threshold dynamics, where local elements fail when a critical stress is exceeded, naturally evolve toward a critical state characterized by power-law distributions of event sizes, fractal spatial patterns, and $1/f$ noise in temporal signals. Ecosystems possess precisely these characteristics. Individual organisms have physiological thresholds beyond which function is impaired. Local patches of vegetation have critical water potentials beyond which hydraulic failure occurs. Soil carbon pools have critical temperatures beyond which decomposition accelerates nonlinearly.

Under the baseline energy fluctuation regime to which an ecosystem is adapted, these threshold-crossing events occur at rates that the system can accommodate through recovery processes. Species recolonize disturbed patches. New individuals recruit to replace those lost. Nutrient pools are replenished through weathering and fixation. But when global warming increases the frequency and intensity of threshold-crossing events, e.g., when heatwaves occur more often and with greater severity, when droughts extend beyond the evolved tolerance of the vegetation, and when storms exceed the structural resistance of the canopy, the recovery capacity becomes overwhelmed. The system enters a regime where disturbances propagate across spatial and temporal scales without sufficient recovery intervals.

This is the self-organized critical state (Zhang, 2016). In this state, the system loses its characteristic scale, disturbances of all sizes occur, from the death of a single branch to the collapse of an entire forest stand. More importantly, the system becomes exquisitely sensitive to perturbation. Because the stabilizing feedbacks have been eroded and the energy landscape basin has been compressed to near-flatness, even a minor additional fluctuation can trigger a system-wide reorganization.

The transition from the self-organized critical state to a new steady state constitutes an ecological phase transition (Zhang, 2016, 2026e). The term phase transition is used deliberately to evoke the analogy with physical phase transitions (the freezing of water, and the magnetization of iron, etc.) which occur when a control parameter (temperature, magnetic field) crosses a critical value. Here, the control parameter is the amplitude of energy fluctuations, and the phase transition is the reorganization of ecosystem structure and function into a new configuration.

The formal connection to critical phenomena in statistical physics provides a rich mathematical framework. Near the critical point, the correlation length ξ, i.e., the spatial scale over which fluctuations are correlated, diverges according to:

$$\xi \sim |\Delta E - \Delta E_c|^{-\nu}$$

where ΔE is the energy fluctuation amplitude, ΔE_c is its critical value, and ν is a critical exponent. Similarly, the relaxation time τ, the characteristic time for the system to return to equilibrium, diverges as:

$$\tau \sim |\Delta E - \Delta E_c|^{-\zeta}$$

These divergences imply that as the system approaches the critical point, it becomes simultaneously more spatially coherent (large-scale patterns emerge) and more temporally sluggish (recovery becomes slower). Both phenomena have been observed empirically in ecosystems approaching transitions.

Proposition Three: Maximum Entropy Production Guides the Direction of Phase Transition

When an ecosystem undergoes a phase transition driven by energy fluctuation amplification, the direction of the transition. i.e., the characteristics of the new steady state, is guided by the maximum entropy production principle. The system tends to reorganize into a configuration that dissipates energy more rapidly, which under warming conditions translates to states characterized by faster biomass turnover, greater dominance by organisms with high metabolic rates, simplified trophic structure, and enhanced carbon release to the atmosphere.

This proposition provides the selection criterion that determines which of several possible alternative states the system will adopt following a phase transition. Multiple alternative basins may exist in the energy landscape, e.g., a forest could transition to grassland or to shrubland, and a coral reef could transition to macroalgal dominance or to bare substrate, but the maximum entropy production principle predicts that the system will tend toward the state that maximizes the rate of entropy production under the new energy forcing regime.

The physical basis for this selection lies in the thermodynamics of irreversible processes. For systems maintained far from equilibrium, Prigogine‘s principle of minimum entropy production applies only in the linear regime near equilibrium. In the nonlinear regime far from equilibrium—which is where living systems operate—the behavior is more complex, and a general extremal principle remains elusive (Kondepudi and Prigogine, 2015). However, the maximum entropy production principle has emerged as a powerful heuristic that appears to describe the behavior of a wide range of non-equilibrium systems, from fluid convection to planetary climate to biological evolution (Kleidon and Lorenz, 2005; Martyushev and Seleznev, 2006; Zhang, 2012, 2018).

Applied to ecosystems, the maximum entropy production principle suggests that configurations that dissipate energy more rapidly—that convert ordered, low-entropy solar radiation into disordered, high-entropy heat more efficiently—will be thermodynamically favored. In practical ecological terms, this translates to several specific predictions for warming-driven phase transitions:

(1) Systems should tend toward higher biomass turnover rates. Rapidly growing, short-lived organisms dissipate energy more quickly than slowly growing, long-lived organisms because they cycle carbon and energy through metabolic pathways at higher rates. This explains the widespread observation that disturbed, warming-affected ecosystems are dominated by ruderal species, pioneer vegetation, and opportunistic consumers with short generation times.

(2) Trophic structure should simplify. Each trophic transfer involves an energetic cost (approximately 90% of the energy is lost as heat at each step) so food chains with fewer links dissipate energy more directly. Warming simplifies food-web structure and shortens the pathways of energy flux between consumers and resources, and a simple allometric diet breadth model predicted 68–82% of the observed variation in food chain length (O’Gorman et al., 2019). Higher temperature simplified food-web structure and shortened the pathways of energy flux, reducing the stability of aquatic ecosystems by eroding the structural integrity of the

food web (O’Gorman et al., 2019). Climate warming is predicted to alter routing and flows of energy through food webs because of the critical and varied effects of temperature on physiological rates, community structure, and trophic dynamics (Junker et al., 2024).

(3) Carbon release should accelerate. Biomass represents stored chemical energy that has been temporarily sequestered from dissipation. Under maximum entropy production, the incentive is to mobilize this stored energy and dissipate it as rapidly as possible. This explains the observed acceleration of soil carbon respiration under warming, the enhanced methane emissions from thawing permafrost, and the increasing frequency of carbon-releasing disturbances such as wildfire and insect outbreaks.

These three propositions together form a coherent theoretical structure that can explain the full spectrum of ecosystem responses to global warming. Gradual responses (phenological shifts, range expansions, productivity changes) occur when energy fluctuation amplification remains below the intrinsic critical energy, allowing the system to adjust within its existing structural configuration. Abrupt responses (regime shifts, mass mortality, ecosystem collapse) occur when energy fluctuation amplification exceeds the intrinsic critical energy, driving the system into a self-organized critical state from which it transitions to a new configuration characterized by higher entropy production (Zhang, 2016, 2026e).

4.4 Novel Indices

To realize the framework and enable empirical testing, I propose two novel indices that quantify key aspects of the thermodynamic state of ecosystems.

Energy Sensitivity Index (*ESI*)

The Energy Sensitivity Index quantifies the responsiveness of an ecosystem’s energy dissipation network to perturbations in effective energy input. It measures the degree to which a given change in energy input propagates through the system’s dissipative pathways, and thus the system‘s proximity to its dissipative capacity limits.

Mathematically, the Energy Sensitivity Index is defined as:

$$ESI = \frac{\partial \Phi_{\text{diss}}}{\partial E_{\text{eff}}} \cdot \frac{\sigma(E_{\text{eff}})}{\Phi_{\text{diss}}}$$

where Φ_{diss} is the total energy dissipation rate of the ecosystem, E_{eff} is the effective energy input, and $\sigma(E_{\text{eff}})$ is the standard deviation of effective energy input fluctuations. The first factor, $\frac{\partial \Phi_{\text{diss}}}{\partial E_{\text{eff}}}$, represents the marginal dissipation response, i.e., how much additional dissipation is generated per unit increase in energy input. When the system has spare dissipative capacity, this derivative is large; when the system is operating near its maximum dissipation rate, it approaches zero. The second factor normalizes by the relative fluctuation amplitude, so that a system with low dissipative capacity that also experiences large fluctuations will have a very low *ESI*.

Low values of *ESI* indicate that the ecosystem is operating near its dissipative limits and is therefore vulnerable to energy-fluctuation-driven destabilization. High *ESI* values indicate substantial spare capacity and greater resilience to energy perturbations.

Operationally, *ESI* can be estimated from eddy covariance flux tower data. The total energy dissipation rate Φ_{diss} can be approximated as the sum of sensible and latent heat fluxes, while the effective energy input E_{eff} corresponds to net radiation minus ground heat flux. The marginal response $\frac{\partial \Phi_{\text{diss}}}{\partial E_{\text{eff}}}$ can be estimated from the slope of the regression of dissipation on energy input over a moving time window, and $\sigma(E_{\text{eff}})$ can be calculated as the standard deviation of detrended net radiation over the same window.

Phase Transition Warning Index (*PTI*)

The Phase Transition Warning Index (*PTI*) is designed to detect the approach of an ecosystem to a critical threshold where a phase transition becomes imminent. It builds on the established early warning signal framework based on critical slowing down but extends it by incorporating energy-based metrics that may provide earlier and more specific warnings.

The Phase Transition Warning Index is defined as:

$$PTI = \alpha \cdot \tau_{\text{ac}}(E_{\text{diss}}) + \beta \cdot H(E_{\text{diss}}) + \gamma \cdot D(E_{\text{diss}})$$

where τ_{ac} is the lag-one autocorrelation of the energy dissipation time series, a measure of critical slowing down; H is the Hurst exponent of the energy dissipation time series, a measure of long-range persistence that is expected to increase as the system approaches self-organized criticality; and D is the fractal dimension of the spatial pattern of energy dissipation, expected to decrease as the system becomes more spatially correlated near criticality. The coefficients α, β, and γ are weights that can be estimated from training data or theoretical considerations.

PTI is designed to increase monotonically as the system approaches a critical threshold. When *PTI* exceeds an empirically or theoretically determined threshold value, a phase transition is considered to be imminent, and management interventions may be warranted.

The innovation of *PTI* relative to existing early warning signals is its grounding in energy rather than state variables. State variables such as biomass, species abundance, or vegetation cover may exhibit complex dynamics that obscure the approach to criticality. Energy dissipation, as the fundamental process that drives ecosystem dynamics, may provide a cleaner signal. Moreover, energy dissipation integrates across all the processes that contribute to ecosystem function, potentially providing a more holistic indicator of system stability than any single state variable.

5 Reasoning and Multiple Lines of Evidence

5.1 Thermodynamic Logical Foundations

The theoretical framework advanced here rests on the second law of thermodynamics and its extension to open, far-from-equilibrium systems. The second law states that the total entropy of an isolated system never decreases. For open systems that exchange energy and matter with their surroundings, the change in entropy can be decomposed as:

$$dS = d_eS + d_iS$$

where d_eS is the entropy exchange with the environment (which can be positive or negative) and $d_iS \geq 0$ is the internal entropy production, which is always non-negative by the second law. Ecosystems, as open systems, maintain their low-entropy, high-order structure by exporting entropy to their surroundings at a rate that compensates for internal entropy production.

Under steady-state conditions, the entropy of the system remains constant $dS = 0$, implying that entropy export exactly balances internal entropy production:

$$-\, d_e S = d_i S > 0$$

The system thus maintains a steady rate of entropy production and export. This steady state is not thermodynamic equilibrium, which would require $d_i S = 0$, but a non-equilibrium stationary state maintained by the continuous throughput of energy.

Global warming perturbs this steady state by increasing the energy throughput. The additional energy must be dissipated, increasing the required rate of entropy production. If the existing ecosystem structure can accommodate this increase (if there is spare dissipative capacity), the system can adjust while maintaining its structural integrity. This corresponds to the gradual ecological responses documented extensively in the literature: increased metabolic rates, faster growth, enhanced productivity.

However, there exists a fundamental limit to how much entropy production a given ecosystem structure can sustain. This limit is set by the maximum rate at which energy can be processed through the existing metabolic and physical pathways of the system. When the required entropy production rate exceeds this maximum, the existing structure becomes thermodynamically unsustainable. The system must either find new dissipative pathways, which may involve structural reorganization, or experience degradation as energy accumulates in forms that cannot be dissipated through existing channels.

This thermodynamic argument explains why ecosystems exhibit threshold responses to warming. Below the dissipative capacity limit, responses are gradual and proportional. Above this limit, the system is forced into a regime where structural reorganization is the only thermodynamically viable option. The reorganization toward a state of higher entropy production is not merely one possible outcome; it is, in a thermodynamic sense, the inevitable response of a dissipative system to energy forcing that exceeds its current dissipative capacity.

The maximum entropy production principle provides further insight into the direction of this reorganization. While the theoretical status of maximum entropy production as a universal principle remains debated, it has substantial empirical support and a plausible physical basis (Kleidon and Lorenz, 2005; Martyushev and Seleznev, 2006; Zhang, 2012, 2016, 2018). If ecosystems tend toward states that maximize entropy production under given constraints, then warming-driven reorganization should consistently move systems toward configurations with higher entropy production rates. The empirical evidence reviewed earlier—simplification of trophic structure, dominance by fast-turnover species, accelerated carbon release—is fully consistent with this prediction.

5.2 Metabolic Ecology Derivations

The metabolic theory of ecology provides the quantitative bridge between individual-level metabolic responses to temperature and ecosystem-level energy dynamics. Starting from the fundamental metabolic scaling relationship (Brown et al., 2004):

$$B = b_0\, M^{3/4}\, \mathrm{e}^{-E/(kT)}$$

where B is individual metabolic rate, M is body mass, E is the activation energy of metabolic reactions (approximately 0.65 eV), k is Boltzmann’s constant, and T is absolute temperature, the total metabolic rate of an ecosystem can be obtained by summing over all individuals across all species.

For an ecosystem at steady state, the total metabolic energy dissipation, i.e., the rate at which chemical energy is converted to heat through respiration, is given by:

$$\Phi_{\text{resp}} = \sum_j \sum_i N_{ij}\, b_0\, M_{ij}^{3/4}\, \mathrm{e}^{-E/(kT)}$$

where N_{ij} is the abundance of individuals of species j in size class i, and M_{ij} is their body mass. This quantity represents a substantial fraction of the total energy dissipated by the ecosystem.

The temperature sensitivity of total ecosystem respiration follows directly from the temperature dependence of individual metabolic rates. Differentiating with respect to temperature yields:

$$\frac{\partial \ln \Phi_{\text{resp}}}{\partial T} = \frac{E}{kT^2} + \sum_j \sum_i \frac{\partial \ln(N_{ij}\, M_{ij}^{3/4})}{\partial T}$$

The first term, $\frac{E}{kT^2}$, is the direct thermodynamic effect: at biologically relevant temperatures, a 1°C warming increases metabolic rate by approximately 6-7%. The second term represents the indirect effects of temperature on population size and size structure, which may amplify or counteract the direct effect depending on ecological context.

The critical insight for understanding ecosystem responses to warming is the concept of metabolic balance, i.e., the ratio of total respiration to total production. Gross primary production is also temperature-dependent, but its temperature sensitivity is generally lower than that of respiration (Yvon-Durocher et al., 2012). The differential temperature sensitivities create a metabolic imbalance that grows with warming:

$$\frac{R}{P} = \frac{R_0 \mathrm{e}^{-E_R/(kT)}}{P_0 \mathrm{e}^{-E_P/(kT)}} = \frac{R_0}{P_0} \mathrm{e}^{-(E_R - E_P)/(kT)}$$

where $\frac{R}{P}$ is the respiration-to-production ratio, E_R and E_P are the activation energies for respiration and production respectively, and $E_R > E_P$. As temperature increases, the respiration-to-production ratio increases exponentially, progressively reducing the net carbon uptake of the ecosystem. When $\frac{R}{P}$ exceeds unity, the ecosystem transitions from carbon sink to carbon source.

This metabolic imbalance analysis provides a mechanistic explanation for the observed saturation and reversal of carbon sinks under warming. It also connects directly to the thermodynamic framework: the increasing $\frac{R}{P}$ ratio represents increasing entropy production per unit of energy capture, consistent with the maximum entropy production tendency.

5.3 Statistical Physics Support

The mathematical framework of statistical physics, particularly the theory of critical phenomena and phase transitions, provides powerful tools for analyzing ecosystem dynamics near critical thresholds. The analogy between ecosystem state transitions and physical phase transitions is not merely metaphorical; it rests on deep structural similarities in the underlying mathematics.

Consider an ecosystem described by a set of state variables $\mathbf{x} = (x_1, x_2, ..., x_n)$ representing, for instance, the biomasses of different functional groups. The dynamics can be described by a Langevin equation:

$$\frac{d\mathbf{x}}{dt} = \mathbf{f}(\mathbf{x},\lambda) + \mathbf{g}(\mathbf{x},\lambda) \cdot \boldsymbol{\xi}(t)$$

where **f** represents deterministic dynamics, λ is a control parameter (here, the energy fluctuation amplitude), **g** is a noise amplitude matrix, and $\boldsymbol{\xi}(t)$ is a vector of independent Gaussian white noise processes.

The deterministic dynamics **f** can be expressed as the negative gradient of a potential function $V(\mathbf{x}, \lambda)$ plus a non-gradient component representing non-equilibrium forcing:

$$\mathbf{f}(\mathbf{x},\lambda) = -\nabla V(\mathbf{x}, \lambda) + \mathbf{f}_{\mathrm{non-eq}}(\mathbf{x},\lambda)$$

The potential V defines the energy landscape. Stable states correspond to local minima of V, and transitions between states occur when fluctuations (amplified by the noise term) drive the system over the potential barrier separating basins.

As the control parameter λ approaches its critical value λ_c, one of the eigenvalues of the Hessian matrix $\nabla^2 V$ at the current equilibrium approaches zero. This eigenvalue softening corresponds to the flattening of the potential in a particular direction in state space and the direction along which the transition will occur. The rate of approach to equilibrium along this direction slows according to:

$$\tau \sim |\lambda - \lambda_c|^{-1}$$

This is the mathematical origin of critical slowing down. The variance of fluctuations in the direction of the softening eigenmode diverges as:

$$\sigma^2 \sim |\lambda - \lambda_c|^{-1}$$

These statistical signatures, i.e., increasing variance, increasing autocorrelation, and the specific pattern of eigenmode softening, provide the basis for empirical early warning of approaching transitions.

The landscape-flux theory from non-equilibrium statistical mechanics extends this framework by explicitly accounting for the non-equilibrium nature of ecological systems (Xu et al., 2023). In non-equilibrium systems, the driving force cannot be expressed purely as the gradient of a potential; there is also a curl flux component representing the cyclic, irreversible nature of non-equilibrium dynamics. The entropy production rate, which is directly related to the magnitude of this non-equilibrium flux, provides an additional diagnostic of system state that may be more sensitive to approaching transitions than traditional variance-based metrics.

The emergence of long-range spatial correlations near criticality is another prediction of statistical physics that has observable ecological manifestations. As $\lambda \to \lambda_c$, the spatial correlation length diverges, meaning that fluctuations in distant parts of the ecosystem become synchronized. This spatial coherence has been documented in ecosystems approaching transitions (for instance, the increasing spatial synchrony in tree mortality across forest stands prior to widespread dieback events) and provides another potential early warning signal.

5.4 Reinterpretation of Known Abrupt Transition Events

The theoretical framework developed here provides a unified reinterpretation of several well-documented abrupt ecological transitions, revealing the common thermodynamic mechanisms underlying apparently disparate phenomena.

Coral Bleaching as Symbiotic Decoupling Under Energy Overload

Coral bleaching occurs when heat stress causes the breakdown of the symbiosis between coral polyps and their zooxanthellae algae. The conventional explanation focuses on temperature exceeding physiological tolerance, leading to photosynthetic damage and oxidative stress in the symbionts (Wu and Zhang, 2012). The thermodynamic reinterpretation frames bleaching as an energy overload phenomenon.

Under normal conditions, the coral-zooxanthellae symbiosis functions as an efficient energy dissipation system. Solar radiation is captured by zooxanthellae photosynthesis and converted to chemical energy, which powers both symbiont and host metabolism, with excess energy dissipated through fluorescence and heat. This arrangement allows the coral colony to maintain a high rate of energy throughput, and thus entropy production, consistent with its existence as a dissipative structure in the energy-rich, nutrient-poor tropical ocean environment.

When water temperatures exceed the bleaching threshold, the photosynthetic apparatus of the zooxanthellae becomes damaged. Damaged photosystems cannot process captured photons efficiently, leading to the production of reactive oxygen species that cause oxidative damage to both symbiont and host. From a thermodynamic perspective, the energy capture system is receiving more energy than it can process through its normal dissipative pathways. The accumulated excess energy damages the dissipative machinery itself.

The expulsion of zooxanthellae, i.e., bleaching, can be understood as an emergency energy management response. By ejecting the damaged symbionts, the coral eliminates the primary source of oxidative stress, effectively reducing its energy capture to zero. The bleached coral survives on stored energy reserves until conditions improve and new symbionts can be acquired. If the energy overload condition persists too long, the coral starves.

The phase transition framework explains why bleaching events are becoming more frequent and severe. As baseline ocean temperatures rise, corals are operating closer to their bleaching threshold even under normal conditions. The energy fluctuation amplification associated with marine heatwaves more frequently pushes the system beyond the critical threshold where symbiotic decoupling occurs. The transition from healthy to bleached state is abrupt because it is a threshold-crossing phenomenon, not a gradual response proportional to temperature increase.

The post-bleaching trajectory, i.e., whether the coral recovers or the reef transitions to algal dominance, illustrates the maximum entropy production principle in action. Recovery represents a return to the high-dissipation coral-dominated state. Algal dominance represents a transition to a state with higher entropy production: fast-growing turf algae capture and dissipate solar energy more rapidly than slow-growing corals, and the simplified trophic structure that follows reduces the number of energy-transfer steps, increasing the overall rate of energy dissipation. The thermodynamic selection pressure favors the algal-dominated state under persistent warming.

Boreal Forest Mass Mortality as Unified Hydraulic and Carbon Failure

Warming-driven forest mortality events, particularly in boreal and temperate regions, have increased dramatically in frequency and extent over recent decades. These events involve the simultaneous death of trees across large areas and are attributed to a combination of hydraulic failure (water transport collapse under drought stress) and carbon starvation (depletion of carbohydrate reserves due to respiration exceeding photosynthesis).

The thermodynamic framework unifies these mechanisms through the concept of net energy deficit. Trees maintain a positive energy balance when photosynthetic carbon gain exceeds respiratory carbon loss, providing surplus energy for growth, defense, and storage. This energy balance depends critically on the maintenance of hydraulic function: the water transport system must deliver sufficient water to leaves to sustain photosynthesis and to provide evaporative cooling.

Warming stresses this energy balance in multiple simultaneous ways. Higher temperatures increase maintenance respiration, directly reducing the net energy surplus. Higher vapor pressure deficits increase transpiration demand, requiring higher water transport rates to maintain hydration. More frequent and intense droughts reduce soil water availability, constraining water transport. The combination can push trees into a net energy deficit where respiration exceeds photosynthesis and stored reserves are depleted, i.e., carbon starvation. Simultaneously, hydraulic failure can occur if water transport capacity is insufficient to meet transpiration demand, causing desiccation regardless of carbon status.

The transition from apparently healthy forest to widespread mortality is abrupt because it is a threshold-crossing phenomenon. Individual trees can tolerate temporary energy deficits by drawing on reserves, but once reserves are depleted beyond a critical level, recovery is impossible. At the stand scale, the process can exhibit spatial propagation as the death of some trees alters the microclimate in ways that increase stress on survivors.

Post-mortality ecosystem trajectories illustrate the maximum entropy production principle. Dead trees release stored carbon through decomposition, fueling heterotrophic respiration. Regenerating vegetation is typically characterized by fast-growing, early-successional species with higher metabolic rates and faster turnover than the mature forest they replace. The overall effect is a transition from a high-biomass, slow-turnover state to a low-biomass, fast-turnover state with higher specific entropy production rates.

Tundra Shrub Expansion as Transition to Higher Dissipation Structure

Arctic tundra ecosystems have experienced pronounced shrub expansion, often termed shrubification, over recent decades, driven by warming temperatures. Repeat photography, long-term ecological monitoring, and dendrochronology have documented shrub expansion in arctic, high-latitude, and alpine tundra ecosystems (Myers-Smith et al., 2011). This represents a fundamental structural change in one of Earth‘s most extensive biomes.

Conventional explanations focus on temperature limitation of shrub growth, with warming releasing tundra vegetation from cold constraint. The thermodynamic reinterpretation frames shrub expansion as a phase transition toward a higher-dissipation ecosystem configuration.

Low-stature tundra vegetation, i.e., mosses, lichens, graminoids, and prostrate shrubs, represents an energy dissipation configuration adapted to extreme cold. Low stature minimizes heat loss to the atmosphere, and the high albedo of the tundra surface reflects a substantial fraction of incident solar radiation. This configuration maintains relatively low rates of energy throughput and entropy production, consistent with the limited energy available in the cold Arctic environment.

Warming increases the energy available for dissipation. Taller shrubs with greater leaf area can capture and transpire more energy than the low-stature vegetation they replace, increasing the rate of latent heat dissipation. The darker surface of shrub-dominated tundra has lower albedo than the lighter, lichen-dominated surface it replaces, absorbing more solar radiation and further increasing available energy. These changes create a positive feedback: shrub expansion reduces albedo, increasing energy absorption, which further favors shrub growth and expansion.

The transition from low-stature tundra to shrub-dominated vegetation exhibits the characteristics of a phase transition. It involves a qualitative change in ecosystem structure: the addition of a new life form that fundamentally alters energy balance, hydrology, and biogeochemistry. It exhibits hysteresis, with shrub-dominated states potentially resisting reversion to graminoid tundra even if temperatures were to decline, due to the albedo feedback and altered soil conditions. And it is directional, moving the system toward a configuration with higher energy dissipation rates, consistent with the maximum entropy production tendency.

6 Methodological Innovation: Energy Flow Network Construction and Energy Landscape Characterization

6.1 Data Sources and Energy Flow Quantification

Realizing the Ecological Thermodynamic Fluctuation-Phase Transition framework requires quantification of energy flows through ecosystems and their temporal variability. Several existing and emerging data sources can support this quantification.

Eddy covariance flux towers, organized in networks such as FLUXNET, provide direct measurements of ecosystem-atmosphere exchanges of energy, water, and carbon dioxide at half-hourly to hourly temporal resolution. These measurements include net radiation, sensible heat flux, latent heat flux, and CO_2 flux, from which gross primary production and ecosystem respiration can be estimated. Eddy covariance data thus provide the most direct empirical basis for quantifying effective energy input and ecosystem energy dissipation rates. The eddy covariance technique directly measures mass and energy exchange between ecosystems and the atmosphere, and measurements of the Earth‘s surface energy budget using this technique identify the balance between available energy and turbulent heat fluxes (Mauder et al., 2020). Despite well-known challenges with energy balance closure, where available energy frequently exceeds the sum of turbulent fluxes, the technique provides the best available empirical constraint on ecosystem energy dynamics.

Remote sensing products provide the spatial coverage that tower-based measurements lack. Satellite-derived land surface temperature products, particularly from thermal infrared sensors such as those on the ECOsystem Spaceborne Thermal Radiometer Experiment on Space Station, provide high-resolution measurements of surface temperature that can be used to estimate energy fluxes through surface energy balance models (Fisher et al., 2020). The Surface-Air Temperature Difference Anomaly approach uses geostationary satellite thermal data and ground-based gridded climate data to detect the very first signs of plant stress, well before the stress becomes visible (NCI Australia, 2025). Thermal stress, defined as surface-air temperature difference, provides a reliable surrogate for drought-induced water stress in vegetation (Seyednasrollah et al., 2019). Solar-induced chlorophyll fluorescence, measurable from satellite platforms, provides a direct probe of photosynthetic activity and thus of the biological energy capture that drives ecosystem metabolism.

Genomic and transcriptomic data offer the potential to quantify the metabolic potential of ecological communities at unprecedented resolution. Metagenomic sequencing of environmental samples reveals the abundance and diversity of genes encoding key energy metabolism pathways: photosynthesis, respiration, methanogenesis, nitrogen fixation, providing a community-level inventory of metabolic capacity (Zhang, 2020d-e). Metatranscriptomics goes further by measuring the expression of these genes, providing a snapshot of actual metabolic activity rather than just potential. These molecular approaches could enable estimation of ecosystem-level energy metabolism parameters that complement flux measurements, particularly in systems where direct flux measurements are impractical.

6.2 Energy Landscape Reconstruction Algorithm

The energy landscape, i.e., the conceptual mapping of ecosystem stability as a function of effective energy input and its fluctuation characteristics, must be reconstructed from empirical data to be useful for prediction. I propose an algorithm for this reconstruction based on time series analysis of energy flux data.

The algorithm proceeds through several steps:

(1) A long time series of effective energy input $E_{\text{eff}}(t)$ and total ecosystem energy dissipation $\Phi_{\text{diss}}\,(t)$ is assembled from eddy covariance measurements, remote sensing estimates, or model output. The time series should span a period sufficient to capture the relevant range of variability, ideally multiple decades.

(2) The effective energy input time series is decomposed into its slowly varying mean $\langle E_{\mathrm{eff}} \rangle$ (t) and its fluctuation component $\Delta E_{\mathrm{eff}}(t) = E_{\mathrm{eff}}(t)$ - $\langle E_{\mathrm{eff}} \rangle$ (t). The slowly varying mean can be estimated using a low-pass filter or moving average with a window width appropriate to the time scale of interest: annual for long-term trend analysis, seasonal for intra-annual dynamics.

(3) The probability density function of the ecosystem state is estimated from the joint distribution of E_{eff} and Φ_{diss} (t) or other state indicators. In a system with multiple stable states, this probability density function should exhibit multiple modes, each corresponding to a distinct basin of attraction.

(4) The effective potential (the negative logarithm of the probability density) is computed:

$$V(x) = -\ln P(x)$$

where x represents the relevant state variable and $P(x)$ is its probability density. The minima of $V(x)$ correspond to the most probable (and thus stable) states, while the barriers between minima represent the thresholds that must be crossed for a transition to occur.

(5) The dynamics of the potential landscape are tracked over time by applying the algorithm in a moving window. As global warming progresses, the landscape should evolve: basins should become shallower (indicating reduced resilience), new basins may appear (indicating the emergence of alternative stable states), and the relative depths of basins should change (indicating shifts in the relative stability of alternative states).

This algorithm provides a data-driven approach to quantifying the stability properties that the theoretical framework identifies as central to understanding ecosystem responses to warming.

6.3 Phase Transition Warning Index Calculation Procedure

The Phase Transition Warning Index (*PTI*) is computed from energy dissipation time series through the following procedure:

(1) The energy dissipation time series Φ_{diss} (t) is de-trended to remove the slowly varying mean, isolating the fluctuation component. The detrending can be accomplished using a Gaussian kernel smoother with a bandwidth selected to preserve variability at time scales relevant to critical transitions, typically months to years.

(3) The lag-one autocorrelation τ_{ac} of the detrended series is calculated in a moving window. As the system approaches a critical threshold, τ_{ac} is expected to increase due to critical slowing down. The window width must balance the trade-off between statistical reliability (requiring more data points) and temporal resolution (requiring fewer data points).

(3) The Hurst exponent H of the de-trended series is estimated using detrended fluctuation analysis. The Hurst exponent quantifies long-range persistence: $H = 0.5$ indicates uncorrelated white noise; $H > 0.5$ indicates persistent long-range correlations; and $H < 0.5$ indicates anti-persistence. As the system approaches self-organized criticality, H is expected to increase toward values characteristic of $1/f$ noise, around 0.7 to 0.9.

(4) If spatially distributed data are available, the spatial correlation structure of energy dissipation is characterized. The fractal dimension D of the spatial pattern of Φ_{diss} (t) can be estimated using box-counting or variogram methods. As the system approaches criticality, spatial correlations extend over larger scales, reducing the fractal dimension.

(5) The three components are combined into the Phase Transition Warning Index using weights that may be optimized for specific ecosystem types. In the absence of system-specific calibration, equal weighting provides a reasonable default:

$$PTI = \frac{1}{3}\left(\frac{\tau_{ac} - \tau_{ac}^{0}}{\sigma_{\tau}} + \frac{H - H^{0}}{\sigma_{H}} + \frac{D^{0} - D}{\sigma_{D}}\right)$$

where the superscript 0 indicates baseline values estimated from a reference period when the system was considered stable, and the σ terms normalize each component by its historical variability.

When *PTI* exceeds a threshold, which determined either from theoretical considerations or from retrospective analysis of systems that have undergone transitions, an early warning is triggered. The threshold value can be calibrated to balance sensitivity (for detecting true approaching transitions) against specificity (for avoiding false alarms).

7 Model Simulation and Testability Design

7.1 Process-Energy Coupled Model Construction

To test the predictions of the Ecological Thermodynamic Fluctuation-Phase Transition framework, I propose the construction of a Process-Energy Coupled Model that embeds energy balance and maximum entropy production constraints within a traditional dynamic vegetation model framework.

Traditional dynamic vegetation models simulate ecosystem processes, photosynthesis, respiration, allocation, mortality, competition, as functions of environmental drivers including temperature, precipitation, radiation, and CO_2 concentration. These models can reproduce many observed patterns of ecosystem response to environmental change but typically do not incorporate thermodynamic constraints or the tendency toward maximum entropy production.

The Process-Energy Coupled Model extends this framework by adding three key components:

(1) An explicit energy balance module tracks all energy fluxes through the ecosystem: net radiation absorption, sensible and latent heat exchange, and the chemical energy fixed in biomass and subsequently released through respiration. This module enforces energy conservation and provides the energy dissipation rate Φ_{diss} as a diagnostic output.

(2) A maximum entropy production constraint is imposed on the allocation of assimilated carbon among alternative pathways. Rather than using fixed allocation coefficients, the model allows allocation to shift dynamically toward pathways that increase the rate of energy dissipation, subject to physiological constraints. This implements the tendency identified in Proposition Three.

(3) Stochastic forcing with controlled amplitude is applied to the energy input, representing both natural variability and the enhanced variability associated with global warming. By running simulations with different amplitudes of energy fluctuation, the model can explore the conditions under which gradual versus abrupt responses occur.

The Process-Energy Coupled Model is designed to exhibit emergent steady-state transitions. As the amplitude of energy fluctuations is gradually increased, analogous to the effect of global warming on climate variability, the model ecosystem should initially show gradual adjustments in productivity, species composition, and carbon storage. Above a critical fluctuation amplitude, it should exhibit an abrupt transition to a new steady state characterized by faster turnover, simplified structure, and higher energy dissipation rates.

7.2 Simulation Experiments Under Different Warming Scenarios

A series of simulation experiments can probe the behavior of the Process-Energy Coupled Model under different warming scenarios and test the specific predictions of the theoretical framework.

Experiment 1: Gradual Warming with Constant Variability

In this experiment, mean temperature is increased gradually, for instance, by 0.05°C per year, while the amplitude of energy fluctuations remains constant at baseline levels. The prediction is that the ecosystem should exhibit gradual responses (shifts in species composition, changes in productivity) but no abrupt transition as long as the fluctuation amplitude remains below the intrinsic critical energy.

Experiment 2: Constant Mean Temperature with Increasing Variability

Here, mean temperature is held constant at baseline while the amplitude of energy fluctuations is progressively increased. The theoretical framework predicts that above a critical fluctuation amplitude, the ecosystem should undergo an abrupt phase transition even without any change in mean conditions. This experiment isolates the effect of variability from the effect of the mean, testing a core claim of the framework.

Experiment 3: Combined Gradual Warming and Increasing Variability

This experiment, representing the most realistic scenario, combines gradual increase in mean temperature with increasing amplitude of energy fluctuations. The prediction is that the phase transition should occur at a lower mean temperature than in the constant-variability case, because the combination of mean and variability effects compresses the attractor basin more rapidly.

Experiment 4: Reversal and Hysteresis

After a phase transition has occurred, the forcing conditions are gradually returned to their pre-transition values. The prediction is that the system should exhibit hysteresis, i.e., the transition back to the original state should require substantially different conditions than those at which the forward transition occurred, and in some cases complete reversal may be impossible due to irreversible changes in soil properties, species pools, or biogeochemical conditions.

These simulation experiments generate testable predictions that can guide empirical research. They also provide a platform for exploring the parameter sensitivities and critical thresholds that determine ecosystem vulnerability to warming-driven phase transitions.

7.3 Typical Case Area Validation Design

Empirical validation of the theoretical framework requires application to real ecosystems where abrupt transitions have been documented or are anticipated. I propose validation studies in three contrasting systems that span the range of energy input regimes and that have existing long-term monitoring data.

Case 1: Alaskan Arctic Tundra

The Alaskan Arctic has experienced pronounced warming, approximately twice the global average rate, and has documented shrub expansion, permafrost thaw, and changes in carbon balance. Long-term ecological monitoring at sites such as Toolik Lake provides multi-decadal records of vegetation composition, productivity, and nutrient cycling. Eddy covariance flux towers operated through the Arctic Observatory Network provide energy and carbon flux data. The prediction is that the Phase Transition Warning Index computed from these flux data should show increasing values over the monitoring period, indicating progressive approach to a critical threshold, and that spatial patterns of shrub expansion should correlate with areas of highest energy fluctuation amplification.

Case 2: Australian Temperate Reefs

The kelp forest ecosystems of the Australian temperate coastline underwent a rapid, well-documented regime shift following the 2011 marine heatwave, transitioning from kelp dominance to turf algae dominance across approximately 100 km of coastline (Wernberg et al., 2016). Pre-existing monitoring data on kelp cover, sea temperature, and herbivore abundance provide a baseline against which to test the predictions of the framework. The retrospective analysis should show that energy fluctuation metric, specifically the frequency and intensity of marine heatwaves, increased in the years preceding the transition, and that the Energy Sensitivity Index declined as the system approached its dissipative capacity limit.

Case 3: Amazon Forest Drought Sensitivity

The Amazon rainforest has experienced several severe droughts since 2005, with observed changes in forest structure, carbon balance, and mortality rates. Long-term forest inventory plots, flux tower measurements, and satellite remote sensing provide complementary data streams for characterizing energy dynamics and ecosystem state. The prediction is that forests in regions with higher energy fluctuation amplification, i.e., areas experiencing more frequent and intense drought, should show greater evidence of approaching criticality, as measured by the Phase Transition Warning Index, and that the spatial pattern of declining resilience should match the pattern of energy fluctuation intensification.

For each case study, the validation approach involves: (a) assembling long-term data on energy fluxes and ecosystem state; (b) computing the Energy Sensitivity Index and Phase Transition Warning Index over time; (c) testing whether these indices show statistically significant trends prior to documented transitions; and (d) comparing the predictive performance of these energy-based indices against traditional state-variable-based early warning signals.

8 Discussion

8.1 Paradigm Shift for Ecological Conservation

The Ecological Thermodynamic Fluctuation-Phase Transition framework carries profound implications for ecological conservation and management. Current conservation paradigms are largely organized around protecting species, habitats, and ecosystem services from degradation, with management interventions designed to maintain or restore historical baseline conditions. The Resist-Accept-Direct framework formalizes the management alternatives of resisting, accepting, or directing ecological transformations as climate change facilitates significant and persistent ecological transformations (Siegel et al., 2024). Yet these paradigms lack a theoretical foundation that can predict when transformations are likely, how they will unfold, and what the outcomes will be.

The thermodynamic framework provides this foundation by reframing conservation from managing species to managing energy flows. The fundamental conservation objective becomes maintaining ecosystems in low-entropy, high-order configurations (the states that support high biodiversity, complex structure, and substantial carbon storage) by controlling the effective energy input rate and, crucially, its fluctuation amplitude. This reframing yields concrete management implications:

(1) It suggests that reducing energy fluctuation amplification may be more effective for preventing abrupt transitions than mitigating mean warming alone. While global mean temperature targets such as 1.5°C or 2°C are important, they may not adequately capture the risk of phase transitions driven by variability increases. Management strategies that buffer ecosystems against extreme events, e.g., maintaining hydrological connectivity, preserving microclimatic refugia, protecting structural complexity, may be particularly effective at preventing transitions.

(2) It implies that fixed warming targets should be complemented by dynamic thresholds based on continuous monitoring of ecosystem energy dynamics. The Phase Transition Warning Index could provide a real-time indicator of ecosystem proximity to critical thresholds, enabling adaptive management that intensifies interventions as the risk of transition increases. This represents a shift from static, target-based conservation to dynamic, risk-based management.

(3) It suggests that in some cases, accepting or directing ecological transformation toward higher-dissipation states may be the only viable management option when energy forcing has already pushed the system past its critical threshold. In these situations, management efforts should focus on guiding the transition toward a new state that, while different from the historical reference, retains key functional attributes and continues to provide essential ecosystem services.

8.2 A New Carbon-Energy Coupling Perspective

The framework offers a novel perspective on the carbon-cycle feedback to climate change. The conventional understanding of the carbon-climate feedback focuses on the temperature sensitivity of carbon cycle processes:

warming increases respiration, releasing CO_2, which causes further warming in a positive feedback loop. This understanding is correct as far as it goes, but it is incomplete.

The thermodynamic perspective reveals that the carbon-climate feedback is fundamentally an energy feedback. The additional CO_2 in the atmosphere traps more outgoing longwave radiation, increasing the energy retained in the Earth system. This additional energy drives ecosystems toward higher-dissipation states characterized by faster carbon turnover and greater carbon release. The carbon release is not merely a passive consequence of warming-increased respiration rates; it is an active thermodynamic response of ecosystems reorganizing to dissipate energy more effectively.

This energy-centered perspective helps explain several otherwise puzzling features of the carbon-climate feedback. The observation that permafrost carbon release could be substantially larger than predicted by gradual thaw models alone, because abrupt thaw processes affecting less than 20% of the permafrost zone could affect half of permafrost carbon, is naturally explained by the phase transition framework. The abrupt thaw represents a threshold-crossing event where the energy input exceeds the system‘s dissipative capacity in its frozen state, triggering a rapid transition to a thawed state with much higher carbon release rates.

Similarly, the observation that forest mortality events can transform carbon sinks into carbon sources virtually overnight, rather than gradually, reflects the threshold dynamics inherent in phase transitions. Once the critical energy deficit threshold is crossed, the entire cohort of stressed trees may die within a single season, releasing carbon through decomposition that had been stored over decades or centuries.

The implication is that carbon cycle projections that do not account for abrupt, threshold-crossing responses may substantially underestimate the strength of the carbon-climate feedback. Climate models that represent only gradual responses to warming may miss the most impactful carbon cycle changes, those associated with ecosystem phase transitions.

8.3 Limitations

The framework developed here has several important limitations that must be acknowledged:

(1) The translation of thermodynamic principles to ecological systems involves significant simplification. Real ecosystems are vastly more complex than the physical systems for which non-equilibrium thermodynamics was developed. They involve millions of interacting species, each with its own physiological characteristics and evolutionary history; spatial heterogeneity at scales from centimeters to continents; and biogeochemical cycles that couple the biosphere to the atmosphere, hydrosphere, and lithosphere. Reducing this complexity to a small number of thermodynamic state variables necessarily discards information. Whether the discarded information is essential for predicting ecosystem behavior remains an open empirical question.

(2) The framework does not adequately account for evolutionary adaptation. Organisms are not passive thermodynamic machines; they evolve in response to selection pressures, and rapid evolution can substantially alter ecological dynamics on time scales relevant to global warming. Eco-evolutionary dynamics, where ecological processes drive rapid evolution while evolved traits immediately reshape ecological interactions, generate tightly coupled feedbacks that govern system trajectories in real time (Zhang, 2026d-e). While some species face extinction risk, several studies have demonstrated the possibility that fast evolution may allow species adaptation and survival despite environmental change (Mosoh, 2026). If evolutionary adaptation can increase the dissipative capacity of existing ecosystem structures, it could delay or prevent phase transitions that would otherwise occur. Incorporating evolutionary dynamics into the thermodynamic framework is an important direction for future development.

(3) The framework currently treats energy fluctuation as a single control variable, but real ecosystems are subject to multiple interacting global change factors, rising CO_2, nitrogen deposition, land-use change, and invasive species, that may affect stability properties in complex, non-additive ways. The compound effects of

climate change, combined with deforestation, agricultural expansion, and urbanization as well as air, water, and soil pollution, could increase risks beyond those captured by any single-factor analysis (IPCC, 2022). Extending the framework to multiple stressors requires characterizing how each stressor affects the energy landscape, both independently and in combination.

(4) The maximum entropy production principle, while providing a useful heuristic for predicting the direction of phase transitions, lacks the status of a rigorous physical law. Whether maximum entropy production can be derived from more fundamental principles, or whether it represents an empirical regularity of limited applicability, remains debated. Pending resolution of this debate, predictions based on maximum entropy production should be treated as hypotheses to be tested rather than as established facts.

(5) The realization of the framework through the Energy Sensitivity Index and Phase Transition Warning Index requires long-term, high-quality data on ecosystem energy fluxes that are currently available for only a limited number of sites. Extending the empirical basis of the framework will require continued investment in flux observation networks, remote sensing capabilities, and data integration platforms.

9 Conclusion

9.1 Core Contributions

This paper has developed and systematically argued for a novel theoretical framework for understanding ecosystem responses to global warming. The Ecological Thermodynamic Fluctuation-Phase Transition framework makes three core contributions to ecological theory and global change science:

(1) It provides a first-principles foundation for ecosystem response theory grounded in non-equilibrium thermodynamics. By treating ecosystems as dissipative structures maintained by energy flow and global warming as a perturbation to that energy flow, the framework derives predictions about ecosystem behavior from fundamental physical constraints rather than from empirical correlations. This represents a step toward the long-sought goal of a predictive ecology based on first principles.

(2) It unifies the explanation of gradual and abrupt ecological responses to warming within a single theoretical structure. Gradual responses, including species range shifts, phenological changes, productivity trends, occur when energy fluctuation amplification remains within the dissipative capacity of the existing ecosystem structure. Abrupt responses, i.e., regime shifts, mass mortality, and ecosystem collapse, etc., occur when energy fluctuation amplification exceeds this capacity, driving the system across a critical threshold. The same thermodynamic principles govern both response modes, with the difference being quantitative rather than qualitative.

(3) It provides operational tools—the Energy Sensitivity Index and the Phase Transition Warning Index—that translate the theoretical framework into empirically measurable quantities. These indices can be computed from existing and emerging data sources, enabling the framework to be tested, refined, and ultimately applied to real-world conservation and management challenges.

9.2 Implications for Global Change Ecology

The framework developed here has the potential to reshape how ecologists think about, study, and manage ecosystem responses to global warming. Several implications are particularly significant.

The framework implies that monitoring ecosystem energy dynamics should become a central component of global change observation systems. Current monitoring emphasizes state variables, e.g., species abundance, vegetation cover, carbon stocks, which describe what an ecosystem is. The thermodynamic framework suggests that monitoring should also emphasize process variables, i.e., energy fluxes, dissipation rates, fluctuation characteristics, which describe what an ecosystem is doing. A shift from observing state to observing energy flow could provide earlier and more specific warnings of approaching transitions.

The framework suggests that the search for universal early warning signals of ecological transitions should focus on energy-based metrics. While statistical signatures such as increasing variance and autocorrelation have proven useful, they are symptoms rather than causes of approaching transitions. Energy-based metrics that directly probe the thermodynamic state of the system may provide more fundamental and more reliable warnings.

The framework calls for the establishment of a global ecosystem energy dynamics monitoring network that integrates flux tower measurements, satellite remote sensing, and ecological observations to provide real-time information on the thermodynamic state of Earth's ecosystems. Such a network would enable systematic testing of the framework's predictions, identification of ecosystems at greatest risk of phase transitions, and evaluation of management interventions designed to maintain ecosystems in desired states.

Ultimately, the framework offers a unifying perspective on one of the most pressing challenges of our time. Global warming is, at its deepest level, an energy problem: human activities are altering the energy balance of an entire planet. Ecosystems, as the living fabric that covers much of that planet, must respond to this energy perturbation according to the laws that govern all energy-driven systems. By understanding these laws and their ecological manifestations, we may yet learn to navigate the challenging transition that lies ahead.

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Appendix
Core Computational Methods

A.1 Derivation of Basin Compression Metrics

The dynamics of an ecosystem in an energy landscape can be described by the overdamped Langevin equation:

$$\frac{dx}{dt} = -\frac{1}{\gamma}\frac{\partial V(x,E_{\mathrm{eff}})}{\partial x} + \sqrt{2D(E_{\mathrm{eff}})}\cdot\eta(t)$$

where x is the ecosystem state variable, γ is a friction coefficient, $V(x, E_{\mathrm{eff}})$ is the effective potential, $D(E_{\mathrm{eff}})$ = $\kappa_B T_{\mathrm{eco}}/\gamma$ is the effective diffusion coefficient with T_{eco} representing the ecological temperature, and $\eta(t)$is Gaussian white noise with $\langle\eta(t)\rangle = 0$ and $\langle\eta(t)\eta(t')\rangle = \delta(t-t')$\).

The potential V can be approximated near a stable equilibrium x_0 as:

$$V(x, E_{\mathrm{eff}}) \approx V(x_0, E_{\mathrm{eff}}) + \frac{1}{2}\kappa(E_{\mathrm{eff}})(x - x_0)^2$$

where $\kappa(E_{\mathrm{eff}}) = \partial^2 V/\partial x^2|_{x_0}$ is the curvature at the equilibrium. The basin depth ΔV, i.e., the potential difference between the equilibrium and the saddle point separating it from the adjacent basin, is given by:

$$\Delta V(E_{\mathrm{eff}}) = V(x_{\mathrm{saddle}}, E_{\mathrm{eff}}) - V(x_0, E_{\mathrm{eff}})$$

As E_{eff} increases, κ decreases and ΔV decreases, representing basin compression. The mean first passage time τ for escape from the basin follows the Kramers approximation:

$$\tau \approx \frac{2\pi\gamma}{\sqrt{\kappa(E_{\mathrm{eff}})|\kappa_{\mathrm{saddle}}(E_{\mathrm{eff}})|}}\exp\left(\frac{\Delta V(E_{\mathrm{eff}})}{\kappa_B T_{\mathrm{eco}}}\right)$$

where κ_{saddle} is the curvature at the saddle point. This equation shows that basin compression (reduction of ΔV) leads to exponentially faster escape rates, explaining the abrupt nature of phase transitions.

A.2 Calculation of Ecosystem Entropy Production Rate

The total entropy production rate of an ecosystem can be estimated from its energy balance. For a terrestrial ecosystem, the primary energy input is net radiation R_n, and the primary dissipation pathways are sensible heat flux H, latent heat flux λ_{E}, and the chemical energy stored in net primary production NPP that is subsequently dissipated through respiration.

The entropy production rate associated with the conversion of solar radiation to heat is:

$$\dot{S}_{\text{rad}} = R_n\left(\frac{1}{T_{\text{surf}}} - 1/T_{\text{sun}}\right)$$

where T_{surf} is the surface temperature and $T_{\text{sun}} \approx 5760\text{K}$ is the solar photosphere temperature.

The entropy production rate associated with evapotranspiration is:

$$\dot{S}_{\text{et}} = \lambda_{\text{E}}\left(\frac{1}{T_{\text{surf}}} - 1/T_{\text{dew}}\right)$$

where T_{dew} is the dew point temperature.

The entropy production rate associated with biological metabolism is:

$$\dot{S}_{\text{bio}} = \frac{R_{\text{eco}}}{T_{\text{surf}}}$$

where R_{eco} is ecosystem respiration. The total entropy production rate is the sum of these contributions:

$$\dot{S}_{\text{total}} = \dot{S}_{\text{rad}} + \dot{S}_{\text{et}} + \dot{S}_{\text{bio}}$$

All quantities can be estimated from eddy covariance measurements.

A.3 Critical Slowing Down Parameter Estimation

The recovery rate λ of an ecosystem following perturbation can be estimated from the lag-one autocorrelation of the detrended state variable:

$$\rho_1 = \frac{\langle (x_t - \bar{x})(x_{t-1} - \bar{x}) \rangle}{\sigma_x^2}$$

For a system governed by linearized dynamics near equilibrium, the recovery rate relates to the autocorrelation as:

$$\lambda = -\frac{1}{\Delta t} \ln \rho_1$$

where Δt is the sampling interval. As the system approaches a critical threshold, $\lambda \to 0$ and $\rho_1 \to 1$.

The variance of the state variable is also expected to increase near criticality:

$$\sigma_x^2 \approx \frac{\sigma_\eta^2}{2\lambda}$$

where σ_η^2 is the variance of the stochastic forcing. The combination of increasing variance and increasing autocorrelation provides a robust signature of approaching criticality.

A.4 Hurst Exponent Calculation via De-trended Fluctuation Analysis

The Hurst exponent H is estimated using de-trended fluctuation analysis (DFA) as follows:

(1) The time series x_t of length N is integrated: $y_k = \sum_{t=1}^{k}(x_t - \bar{x})$ for $k = 1, ..., N$.

(2) The integrated series is divided into non-overlapping segments of length s.

(3) Within each segment, a polynomial trend (typically linear) is fitted and subtracted to obtain the de-trended fluctuation $F^2(\nu, s)$ for segment ν.

(4) The root-mean-square fluctuation is computed as:

$$F(s) = \sqrt{\frac{1}{N_s}\sum_{\nu=1}^{N_s} F^2(\nu, s)}$$

(5) Steps 2-4 are repeated for a range of segment lengths s.

(6) The Hurst exponent is estimated from the scaling relationship:

$$F(s) \propto s^H$$

For uncorrelated white noise, $H = 0.5$; for long-range persistent processes, $0.5 < H < 1$; and for anti-persistent processes, $0 < H < 0.5$. Systems approaching self-organized criticality are expected to exhibit H in the range 0.7-0.9.

A.5 Fractal Dimension Estimation via Box-Counting

For spatially distributed energy dissipation data, the fractal dimension D is estimated using the box-counting method:

(1) The spatial domain is divided into a grid of boxes of side length ϵ.

(2) For each box, the energy dissipation rate is computed; boxes with dissipation above a threshold are counted.

(3) The number of occupied boxes $N(\epsilon)$ is recorded.

(4) Steps 1-3 are repeated for a range of box sizes ϵ.

(5) The fractal dimension is estimated from:

$$D = -\log N(\epsilon)/\log \epsilon$$

A value of $D = 2$ indicates space-filling (Euclidean) behavior, while $D < 2$ indicates fractal clustering. As the system approaches criticality, long-range correlations reduce D toward values characteristic of the critical point.